autogluon_each_location

October 19, 2023

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*30
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

use_groups = False
n_groups = 8

auto_stack = False
num_stack_levels = 0
num_bag_folds = 8
num_bag_sets = 20

use_tune_data = True
use_test_data = True
tune_and_test_length = 0.5 # 3 months from end
holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False#
sample_weight_estimated = 1
sample_weight_may_july = 1

run_analysis = True


shift_predictions_by_average_of_negatives_then_clip = False
```

```
clip_predictions = True
shift_predictions = False
```

[2]:
```
import pandas as pd
import numpy as np




import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
 ↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
       'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
       'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    X_shifted = X[X.index.minute==0][columns].copy()
    # loop through all rows and check if index + 1 hour is in the index, if so␣
 ↪get that value, else nan
    count1 = 0
    count2 = 0
    for i in range(len(X_shifted)):
        if X_shifted.index[i] + pd.Timedelta('1 hour') in X.index:
            count1 += 1
            X_shifted.iloc[i] = X.loc[X_shifted.index[i] + pd.Timedelta('1␣
 ↪hour')][columns]
        else:
            count2 += 1
            X_shifted.iloc[i] = np.nan

    print("COUNT1", count1)
    print("COUNT2", count2)

    X_old_unshifted = X[X.index.minute==0][columns]
    # rename X_old_unshifted columns to have _not_shifted at the end
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
 ↪columns]

    # put the shifted columns back into the original dataframe
```

```python
    #X[columns] = X_shifted[columns]



    date_calc = None
    if "date_calc" in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']

    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column
    ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
```

```python
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
 ↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
 ↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
```

```
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
↪right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Processing location C…
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
```

1 Feature enginering

[3]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
 ↪inplace=True)


for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

#print(X_train.head())


# If the "sample_weight" column is present and weight_evaluation is True,␣
 ↪multiply sample_weight with sample_weight_may_july if the ds is between␣
 ↪05-01 00:00:00 and 07-03 23:00:00, else add sample_weight as a column to␣
 ↪X_train
if weight_evaluation:
    if "sample_weight" not in X_train.columns:
        X_train["sample_weight"] = 1

    X_train.loc[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
 ↪((X_train.index.month == 7) & (X_train.index.day <= 3)), "sample_weight"] *=␣
 ↪sample_weight_may_july


print(X_train.iloc[200])
print(X_train[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
 ↪((X_train.index.month == 7) & (X_train.index.day <= 3))].head(1))


if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()
```

```
        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())




to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
↪gm3", "air_density_2m:kgm3", "msl_pressure:hPa", "pressure_100m:hPa",␣
↪"pressure_50m:hPa", "clear_sky_rad:W"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
absolute_humidity_2m:gm3              7.825
air_density_2m:kgm3                   1.245
ceiling_height_agl:m            2085.774902
clear_sky_energy_1h:J           1685498.875
clear_sky_rad:W                  452.100006
cloud_base_agl:m                2085.774902
dew_or_rime:idx                         0.0
dew_point_2m:K                   280.549988
diffuse_rad:W                    140.800003
diffuse_rad_1h:J                 538581.625
direct_rad:W                     102.599998
direct_rad_1h:J                 439453.8125
effective_cloud_cover:p           71.849998
elevation:m                             6.0
```

```
fresh_snow_12h:cm                          0.0
fresh_snow_1h:cm                           0.0
fresh_snow_24h:cm                          0.0
fresh_snow_3h:cm                           0.0
fresh_snow_6h:cm                           0.0
is_day:idx                                 1.0
is_in_shadow:idx                           0.0
msl_pressure:hPa                   1026.349976
precip_5min:mm                             0.0
precip_type_5min:idx                       0.0
pressure_100m:hPa                  1013.325012
pressure_50m:hPa                   1019.450012
prob_rime:p                                0.0
rain_water:kgm2                            0.0
relative_humidity_1000hPa:p          77.099998
sfc_pressure:hPa                   1025.550049
snow_density:kgm3                          NaN
snow_depth:cm                              0.0
snow_drift:idx                             0.0
snow_melt_10min:mm                         0.0
snow_water:kgm2                            0.0
sun_azimuth:d                        93.415253
sun_elevation:d                      27.633499
super_cooled_liquid_water:kgm2           0.025
t_1000hPa:K                            282.625
total_cloud_cover:p                  71.849998
visibility:m                         44177.875
wind_speed_10m:ms                        2.675
wind_speed_u_10m:ms                       -2.3
wind_speed_v_10m:ms                       -1.4
wind_speed_w_1000hPa:ms                    0.0
is_estimated                                 0
y                                      2991.12
location                                     A
Name: 2019-06-11 06:00:00, dtype: object
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 22:00:00                       7.7              1.22825

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 22:00:00           1728.949951                    0.0

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 22:00:00              0.0       1728.949951              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
```

```
ds                                                                      …
2019-06-02 22:00:00      280.299988            0.0               0.0  …

                     t_1000hPa:K  total_cloud_cover:p  visibility:m  \
ds
2019-06-02 22:00:00   286.225006                100.0  40386.476562

                     wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 22:00:00                3.6               -3.575

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 22:00:00                 -0.5                      0.0

                     is_estimated    y  location
ds
2019-06-02 22:00:00             0  0.0         A

[1 rows x 48 columns]
```

[4]:
```
# Create a plot of X_train showing its "y" and color it based on the value of␣
↪the sample_weight column.
#import matplotlib.pyplot as plt
#import seaborn as sns
#sns.scatterplot(data=X_train, x=X_train.index, y="y", hue="sample_weight",␣
↪palette="deep", size=3)
#plt.show()
```

[5]:
```
def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

import pandas as pd
import numpy as np

def split_and_shuffle_data(input_data, num_bins, frac1):
    """
    Splits the input_data into num_bins and shuffles them, then divides the␣
↪bins into two datasets based on the given fraction for the first set.

    Args:
        input_data (pd.DataFrame): The data to be split and shuffled.
```

```
        num_bins (int): The number of bins to split the data into.
        frac1 (float): The fraction of each bin to go into the first output␣
↪dataset.

    Returns:
        pd.DataFrame, pd.DataFrame: The two output datasets.
    """
    # Validate the input fraction
    if frac1 < 0 or frac1 > 1:
        raise ValueError("frac1 must be between 0 and 1.")

    if frac1==1:
        return input_data, pd.DataFrame()

    # Calculate the fraction for the second output set
    frac2 = 1 - frac1

    # Calculate bin size
    bin_size = len(input_data) // num_bins

    # Initialize empty DataFrames for output
    output_data1 = pd.DataFrame()
    output_data2 = pd.DataFrame()

    for i in range(num_bins):
        # Shuffle the data in the current bin
        np.random.seed(i)
        current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
↪sample(frac=1)

        # Calculate the sizes for each output set
        size1 = int(len(current_bin) * frac1)

        # Split and append to output DataFrames
        output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
        output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # Shuffle and split the remaining data
    remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)
    remaining_size1 = int(len(remaining_data) * frac1)

    output_data1 = pd.concat([output_data1, remaining_data.iloc[:
↪remaining_size1]])
    output_data2 = pd.concat([output_data2, remaining_data.iloc[remaining_size1:
↪]])

    return output_data1, output_data2
```

[6]:

```
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
import numpy as np
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
test_set = TabularDataset(data[data["ds"] >= split_time])

# shuffle test_set and only grab tune_and_test_length percent of it, rest goes␣
↪to train_set
test_set, new_train_set = split_and_shuffle_data(test_set, 40,␣
↪tune_and_test_length)


print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))
print("Length of test set", len(test_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = None
if use_tune_data:
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
```

```
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            # randomly shuffle the loc_test_set
            loc_tuning_data, loc_test_data =␣
↪split_and_shuffle_data(loc_test_set, 40, 0.5)
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
↪the tuning data.
    if weight_evaluation:
        tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        test_data = test_set
        print("Shape of test", test_data.shape[0])


train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
if weight_evaluation:
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
if use_tune_data:
    tuning_data = TabularDataset(tuning_data)
if use_test_data:
    test_data = TabularDataset(test_data)
```

```
Length of train set before adding test set 82026
Length of train set after adding test set 87486
Length of test set 5459
```

```
Shapes of tuning and test 2728 2731 5459
```

[7]:
```python
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data, label="y", sample=None)
```

train_data dataset summary

	count	unique	top	freq	\
ceiling_height_agl:m	72280	59980			
clear_sky_energy_1h:J	87486	46359			
cloud_base_agl:m	81454	61360			
diffuse_rad:W	87486	11092			
diffuse_rad_1h:J	87486	46319			
direct_rad:W	87486	14181			
direct_rad_1h:J	87486	40118			
ds	87486	36794	2021-02-05 14:00:00	3	
effective_cloud_cover:p	87486	5655			
elevation:m	87486	3			
fresh_snow_1h:cm	87486	39			
fresh_snow_3h:cm	87486	70			
fresh_snow_6h:cm	87486	96			
is_day:idx	87486	5			
is_estimated	87486	2			
is_in_shadow:idx	87486	5			
location	87486	3	A	31872	
precip_type_5min:idx	87486	15			
relative_humidity_1000hPa:p	87486	3799			
sfc_pressure:hPa	87486	3795			
snow_depth:cm	87486	487			
snow_water:kgm2	87486	161			
sun_azimuth:d	87486	83179			
sun_elevation:d	87486	72262			
super_cooled_liquid_water:kgm2	87486	53			
t_1000hPa:K	87486	1989			
total_cloud_cover:p	87486	5556			
visibility:m	87486	85949			
wind_speed_10m:ms	87486	596			
y	87486	11321			

	first	last	mean	\
ceiling_height_agl:m	NaT	NaT	2861.929806	
clear_sky_energy_1h:J	NaT	NaT	530297.395771	
cloud_base_agl:m	NaT	NaT	1740.241802	
diffuse_rad:W	NaT	NaT	40.267497	
diffuse_rad_1h:J	NaT	NaT	145328.6257	
direct_rad:W	NaT	NaT	51.524847	
direct_rad_1h:J	NaT	NaT	185338.05854	

```
ds                             2019-01-01 2023-04-30 22:00:00
effective_cloud_cover:p               NaT                 NaT      67.052836
elevation:m                           NaT                 NaT      11.414718
fresh_snow_1h:cm                      NaT                 NaT       0.008783
fresh_snow_3h:cm                      NaT                 NaT       0.026713
fresh_snow_6h:cm                      NaT                 NaT        0.05322
is_day:idx                            NaT                 NaT       0.490147
is_estimated                          NaT                 NaT        0.06241
is_in_shadow:idx                      NaT                 NaT       0.556952
location                              NaT                 NaT
precip_type_5min:idx                  NaT                 NaT       0.084976
relative_humidity_1000hPa:p           NaT                 NaT      73.779918
sfc_pressure:hPa                      NaT                 NaT    1008.035963
snow_depth:cm                         NaT                 NaT       0.197574
snow_water:kgm2                       NaT                 NaT       0.090839
sun_azimuth:d                         NaT                 NaT     179.584247
sun_elevation:d                       NaT                 NaT      -0.705998
super_cooled_liquid_water:kgm2        NaT                 NaT       0.058256
t_1000hPa:K                           NaT                 NaT     279.675551
total_cloud_cover:p                   NaT                 NaT       73.72398
visibility:m                          NaT                 NaT   32944.238197
wind_speed_10m:ms                     NaT                 NaT       3.032943
y                                     NaT                 NaT     294.447861

                                          std      min        25%        50%  \
ceiling_height_agl:m              2532.377528     27.8  1082.3125   1856.075
clear_sky_energy_1h:J           831839.646633      0.0        0.0     9084.9
cloud_base_agl:m                  1808.519208     27.5  598.15625   1174.775
diffuse_rad:W                       61.119566      0.0        0.0       1.35
diffuse_rad_1h:J                218036.296903      0.0        0.0    12531.2
direct_rad:W                       114.236728      0.0        0.0        0.0
direct_rad_1h:J                  406379.39471      0.0        0.0        0.0
ds
effective_cloud_cover:p             34.132847      0.0     42.125       79.7
elevation:m                          7.881545      6.0        6.0        7.0
fresh_snow_1h:cm                     0.110515      0.0        0.0        0.0
fresh_snow_3h:cm                     0.277575      0.0        0.0        0.0
fresh_snow_6h:cm                     0.474579      0.0        0.0        0.0
is_day:idx                           0.486133      0.0        0.0        0.5
is_estimated                           0.2419      0.0        0.0        0.0
is_in_shadow:idx                     0.484138      0.0        0.0        1.0
location
precip_type_5min:idx                  0.32995      0.0        0.0        0.0
relative_humidity_1000hPa:p         14.200631   19.575       64.4      76.15
sfc_pressure:hPa                    13.038723   941.55    1000.05     1009.0
snow_depth:cm                         1.28439      0.0        0.0        0.0
snow_water:kgm2                      0.240248      0.0        0.0        0.0
sun_azimuth:d                       97.419022    6.983    94.4135  180.00663
```

sun_elevation:d	24.006117	-49.932	-17.969875	-0.453875
super_cooled_liquid_water:kgm2	0.106959	0.0	0.0	0.0
t_1000hPa:K	6.551665	258.025	275.1	278.975
total_cloud_cover:p	33.851299	0.0	53.475	92.825
visibility:m	17949.64428	132.375	16564.5125	36910.75
wind_speed_10m:ms	1.758713	0.025	1.675	2.7
y	774.531815	-0.0	0.0	0.0

	75%	max	dtypes \
ceiling_height_agl:m	3916.78125	12285.775	float64
clear_sky_energy_1h:J	831169.675	3006697.2	float64
cloud_base_agl:m	2080.39375	11673.725	float64
diffuse_rad:W	67.15	334.75	float64
diffuse_rad_1h:J	243365.275	1182265.4	float64
direct_rad:W	32.225	683.4	float64
direct_rad_1h:J	122454.125	2445897.0	float64
ds			datetime64[ns]
effective_cloud_cover:p	98.5	100.0	float64
elevation:m	24.0	24.0	float64
fresh_snow_1h:cm	0.0	7.1	float64
fresh_snow_3h:cm	0.0	20.6	float64
fresh_snow_6h:cm	0.0	34.0	float64
is_day:idx	1.0	1.0	float64
is_estimated	0.0	1.0	int64
is_in_shadow:idx	1.0	1.0	float64
location			object
precip_type_5min:idx	0.0	5.0	float64
relative_humidity_1000hPa:p	85.175	100.0	float64
sfc_pressure:hPa	1017.1	1043.725	float64
snow_depth:cm	0.0	18.2	float64
snow_water:kgm2	0.1	5.65	float64
sun_azimuth:d	264.601138	348.48752	float64
sun_elevation:d	16.004499	49.94375	float64
super_cooled_liquid_water:kgm2	0.1	1.375	float64
t_1000hPa:K	284.225	303.25	float64
total_cloud_cover:p	99.9	100.0	float64
visibility:m	48289.05	75326.58	float64
wind_speed_10m:ms	4.05	13.275	float64
y	183.7125	5733.42	float64

	missing_count	missing_ratio	raw_type \
ceiling_height_agl:m	15206	0.173811	float
clear_sky_energy_1h:J			float
cloud_base_agl:m	6032	0.068948	float
diffuse_rad:W			float
diffuse_rad_1h:J			float
direct_rad:W			float
direct_rad_1h:J			float

```
ds                                                               datetime
effective_cloud_cover:p                                             float
elevation:m                                                         float
fresh_snow_1h:cm                                                    float
fresh_snow_3h:cm                                                    float
fresh_snow_6h:cm                                                    float
is_day:idx                                                          float
is_estimated                                                          int
is_in_shadow:idx                                                    float
location                                                           object
precip_type_5min:idx                                                float
relative_humidity_1000hPa:p                                         float
sfc_pressure:hPa                                                    float
snow_depth:cm                                                       float
snow_water:kgm2                                                     float
sun_azimuth:d                                                       float
sun_elevation:d                                                     float
super_cooled_liquid_water:kgm2                                      float
t_1000hPa:K                                                         float
total_cloud_cover:p                                                 float
visibility:m                                                        float
wind_speed_10m:ms                                                   float
y                                                                   float

                               variable_type special_types
ceiling_height_agl:m                 numeric
clear_sky_energy_1h:J                numeric
cloud_base_agl:m                     numeric
diffuse_rad:W                        numeric
diffuse_rad_1h:J                     numeric
direct_rad:W                         numeric
direct_rad_1h:J                      numeric
ds
effective_cloud_cover:p              numeric
elevation:m                         category
fresh_snow_1h:cm                     numeric
fresh_snow_3h:cm                     numeric
fresh_snow_6h:cm                     numeric
is_day:idx                          category
is_estimated                        category
is_in_shadow:idx                    category
location                            category
precip_type_5min:idx                category
relative_humidity_1000hPa:p          numeric
sfc_pressure:hPa                     numeric
snow_depth:cm                        numeric
snow_water:kgm2                      numeric
sun_azimuth:d                        numeric
```

sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	numeric
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
wind_speed_10m:ms	numeric
y	numeric

test_data dataset summary

	count	unique	top	freq	\
ceiling_height_agl:m	2100	2065			
clear_sky_energy_1h:J	2731	1138			
cloud_base_agl:m	2374	2332			
diffuse_rad:W	2731	983			
diffuse_rad_1h:J	2731	1138			
direct_rad:W	2731	750			
direct_rad_1h:J	2731	932			
ds	2731	2200	2023-04-10 19:00:00	3	
effective_cloud_cover:p	2731	1348			
elevation:m	2731	3			
fresh_snow_1h:cm	2731	19			
fresh_snow_3h:cm	2731	36			
fresh_snow_6h:cm	2731	50			
is_day:idx	2731	5			
is_estimated	2731	1			
is_in_shadow:idx	2731	5			
location	2731	3	A	1094	
precip_type_5min:idx	2731	10			
relative_humidity_1000hPa:p	2731	1523			
sfc_pressure:hPa	2731	1575			
snow_depth:cm	2731	61			
snow_water:kgm2	2731	61			
sun_azimuth:d	2731	2716			
sun_elevation:d	2731	2652			
super_cooled_liquid_water:kgm2	2731	29			
t_1000hPa:K	2731	774			
total_cloud_cover:p	2731	1126			
visibility:m	2731	2729			
wind_speed_10m:ms	2731	366			
y	2731	895			

	first	last	\
ceiling_height_agl:m	NaT	NaT	
clear_sky_energy_1h:J	NaT	NaT	
cloud_base_agl:m	NaT	NaT	
diffuse_rad:W	NaT	NaT	
diffuse_rad_1h:J	NaT	NaT	
direct_rad:W	NaT	NaT	

direct_rad_1h:J	NaT	NaT
ds	2022-10-28 22:00:00	2023-04-30 19:00:00
effective_cloud_cover:p	NaT	NaT
elevation:m	NaT	NaT
fresh_snow_1h:cm	NaT	NaT
fresh_snow_3h:cm	NaT	NaT
fresh_snow_6h:cm	NaT	NaT
is_day:idx	NaT	NaT
is_estimated	NaT	NaT
is_in_shadow:idx	NaT	NaT
location	NaT	NaT
precip_type_5min:idx	NaT	NaT
relative_humidity_1000hPa:p	NaT	NaT
sfc_pressure:hPa	NaT	NaT
snow_depth:cm	NaT	NaT
snow_water:kgm2	NaT	NaT
sun_azimuth:d	NaT	NaT
sun_elevation:d	NaT	NaT
super_cooled_liquid_water:kgm2	NaT	NaT
t_1000hPa:K	NaT	NaT
total_cloud_cover:p	NaT	NaT
visibility:m	NaT	NaT
wind_speed_10m:ms	NaT	NaT
y	NaT	NaT

	mean	std	min \
ceiling_height_agl:m	3361.682133	2562.862274	28.0
clear_sky_energy_1h:J	285528.142658	573252.521662	0.0
cloud_base_agl:m	1685.111501	1833.56975	27.5
diffuse_rad:W	26.230813	48.360421	0.0
diffuse_rad_1h:J	94649.301538	172723.786046	0.0
direct_rad:W	32.798068	92.244541	0.0
direct_rad_1h:J	118054.008202	329601.815692	0.0
ds			
effective_cloud_cover:p	66.798654	36.717964	0.0
elevation:m	11.193336	7.806119	6.0
fresh_snow_1h:cm	0.023984	0.147555	0.0
fresh_snow_3h:cm	0.069498	0.352141	0.0
fresh_snow_6h:cm	0.13885	0.57722	0.0
is_day:idx	0.378341	0.472171	0.0
is_estimated	1.0	0.0	1.0
is_in_shadow:idx	0.677133	0.452911	0.0
location			
precip_type_5min:idx	0.076254	0.344931	0.0
relative_humidity_1000hPa:p	71.631472	14.652551	21.7
sfc_pressure:hPa	1009.397775	14.318453	971.15
snow_depth:cm	0.119965	0.56196	0.0
snow_water:kgm2	0.080511	0.19473	0.0

sun_azimuth:d	180.975998	94.222121	14.914
sun_elevation:d	-8.945472	22.095926	-49.887
super_cooled_liquid_water:kgm2	0.035088	0.082444	0.0
t_1000hPa:K	275.52987	4.271781	259.975
total_cloud_cover:p	72.32056	37.085445	0.0
visibility:m	34504.948017	17242.154257	270.3
wind_speed_10m:ms	3.109676	1.782531	0.125
y	179.379421	641.546947	0.0

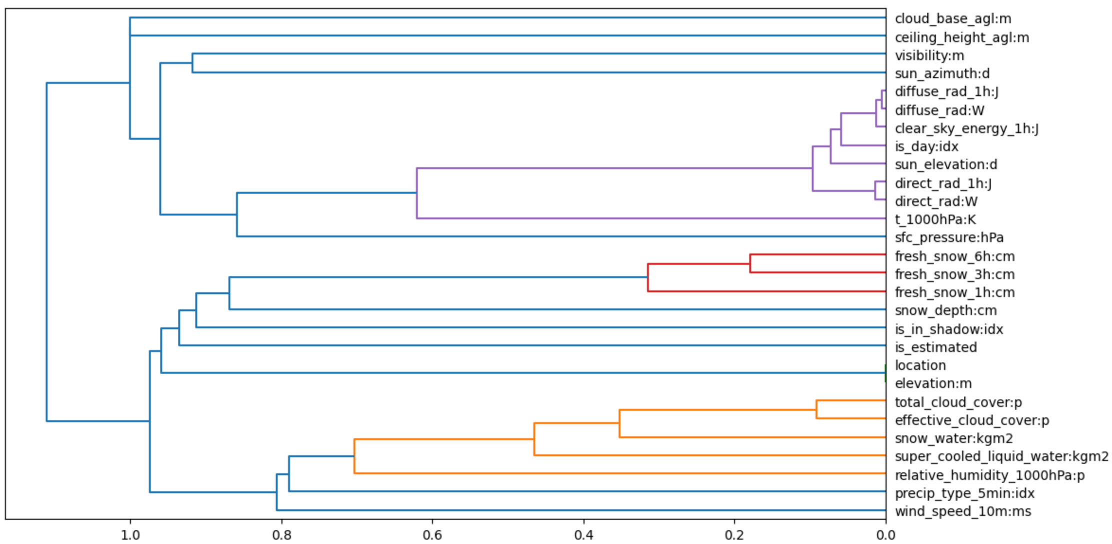
	25%	50%	75%	max \
ceiling_height_agl:m	1245.55625	2784.275	4919.18125	12294.9
clear_sky_energy_1h:J	0.0	0.0	220909.2	2551917.2
cloud_base_agl:m	516.7625	1000.8	2066.9875	10813.7
diffuse_rad:W	0.0	0.0	32.0	280.5
diffuse_rad_1h:J	0.0	0.0	116208.0	986147.0
direct_rad:W	0.0	0.0	4.7625	511.7
direct_rad_1h:J	0.0	0.0	24326.65	1844204.9
ds				
effective_cloud_cover:p	36.3125	83.05	99.825	100.0
elevation:m	6.0	7.0	24.0	24.0
fresh_snow_1h:cm	0.0	0.0	0.0	2.3
fresh_snow_3h:cm	0.0	0.0	0.0	4.8
fresh_snow_6h:cm	0.0	0.0	0.0	6.3
is_day:idx	0.0	0.0	1.0	1.0
is_estimated	1.0	1.0	1.0	1.0
is_in_shadow:idx	0.0	1.0	1.0	1.0
location				
precip_type_5min:idx	0.0	0.0	0.0	3.0
relative_humidity_1000hPa:p	61.775	73.55	82.9625	99.775
sfc_pressure:hPa	999.1	1009.5	1020.275	1040.6
snow_depth:cm	0.0	0.0	0.0	4.9
snow_water:kgm2	0.0	0.0	0.1	2.15
sun_azimuth:d	101.047372	179.89075	260.65412	347.81226
sun_elevation:d	-26.72725	-8.178	6.393625	41.09175
super_cooled_liquid_water:kgm2	0.0	0.0	0.0	0.75
t_1000hPa:K	272.6625	275.45	278.5	285.825
total_cloud_cover:p	44.5875	96.775	100.0	100.0
visibility:m	20902.55	36141.85	48867.949	73937.67
wind_speed_10m:ms	1.6	2.8	4.2375	9.9
y	0.0	0.0	40.397706	5043.72

	dtypes	missing_count	missing_ratio \
ceiling_height_agl:m	float64	631	0.231051
clear_sky_energy_1h:J	float64		
cloud_base_agl:m	float64	357	0.130721
diffuse_rad:W	float64		
diffuse_rad_1h:J	float64		
direct_rad:W	float64		

```
direct_rad_1h:J                           float64
ds                                 datetime64[ns]
effective_cloud_cover:p                   float64
elevation:m                               float64
fresh_snow_1h:cm                          float64
fresh_snow_3h:cm                          float64
fresh_snow_6h:cm                          float64
is_day:idx                                float64
is_estimated                                int64
is_in_shadow:idx                          float64
location                                   object
precip_type_5min:idx                      float64
relative_humidity_1000hPa:p               float64
sfc_pressure:hPa                          float64
snow_depth:cm                             float64
snow_water:kgm2                           float64
sun_azimuth:d                             float64
sun_elevation:d                           float64
super_cooled_liquid_water:kgm2            float64
t_1000hPa:K                               float64
total_cloud_cover:p                       float64
visibility:m                              float64
wind_speed_10m:ms                         float64
y                                         float64

                               raw_type variable_type special_types
ceiling_height_agl:m              float       numeric
clear_sky_energy_1h:J             float       numeric
cloud_base_agl:m                  float       numeric
diffuse_rad:W                     float       numeric
diffuse_rad_1h:J                  float       numeric
direct_rad:W                      float       numeric
direct_rad_1h:J                   float       numeric
ds                             datetime
effective_cloud_cover:p           float       numeric
elevation:m                       float      category
fresh_snow_1h:cm                  float      category
fresh_snow_3h:cm                  float       numeric
fresh_snow_6h:cm                  float       numeric
is_day:idx                        float      category
is_estimated                        int      category
is_in_shadow:idx                  float      category
location                         object      category
precip_type_5min:idx              float      category
relative_humidity_1000hPa:p       float       numeric
sfc_pressure:hPa                  float       numeric
snow_depth:cm                     float       numeric
snow_water:kgm2                   float       numeric
```

sun_azimuth:d	float	numeric
sun_elevation:d	float	numeric
super_cooled_liquid_water:kgm2	float	numeric
t_1000hPa:K	float	numeric
total_cloud_cover:p	float	numeric
visibility:m	float	numeric
wind_speed_10m:ms	float	numeric
y	float	numeric

1.0.1 Feature Distance

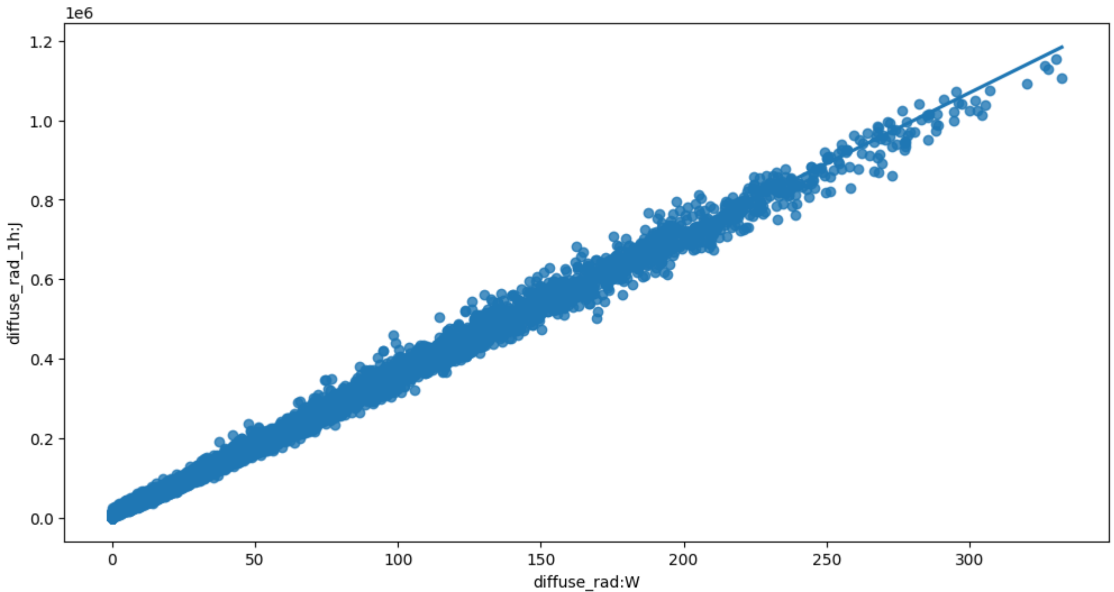


The following feature groups are considered as near-duplicates:

Distance threshold: <= `0.01`. Consider keeping only some of the columns within each group:

- `elevation:m`, `location` - distance `0.00`
- `diffuse_rad:W`, `diffuse_rad_1h:J` - distance `0.00`

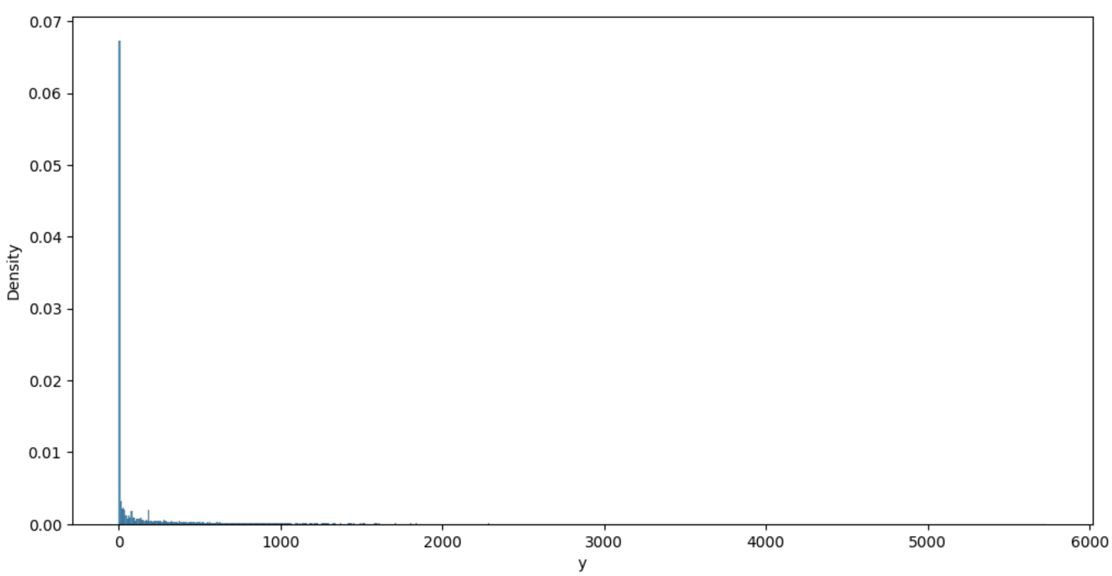
Feature interaction between `diffuse_rad:W`/`diffuse_rad_1h:J`



[8]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

1.1 Target variable analysis

```
   count        mean         std  min  25%  50%       75%      max   dtypes  \
y  87486  294.447861  774.531815 -0.0  0.0  0.0  183.7125  5733.42  float64

   unique missing_count missing_ratio raw_type special_types
y   11321                                 float
```

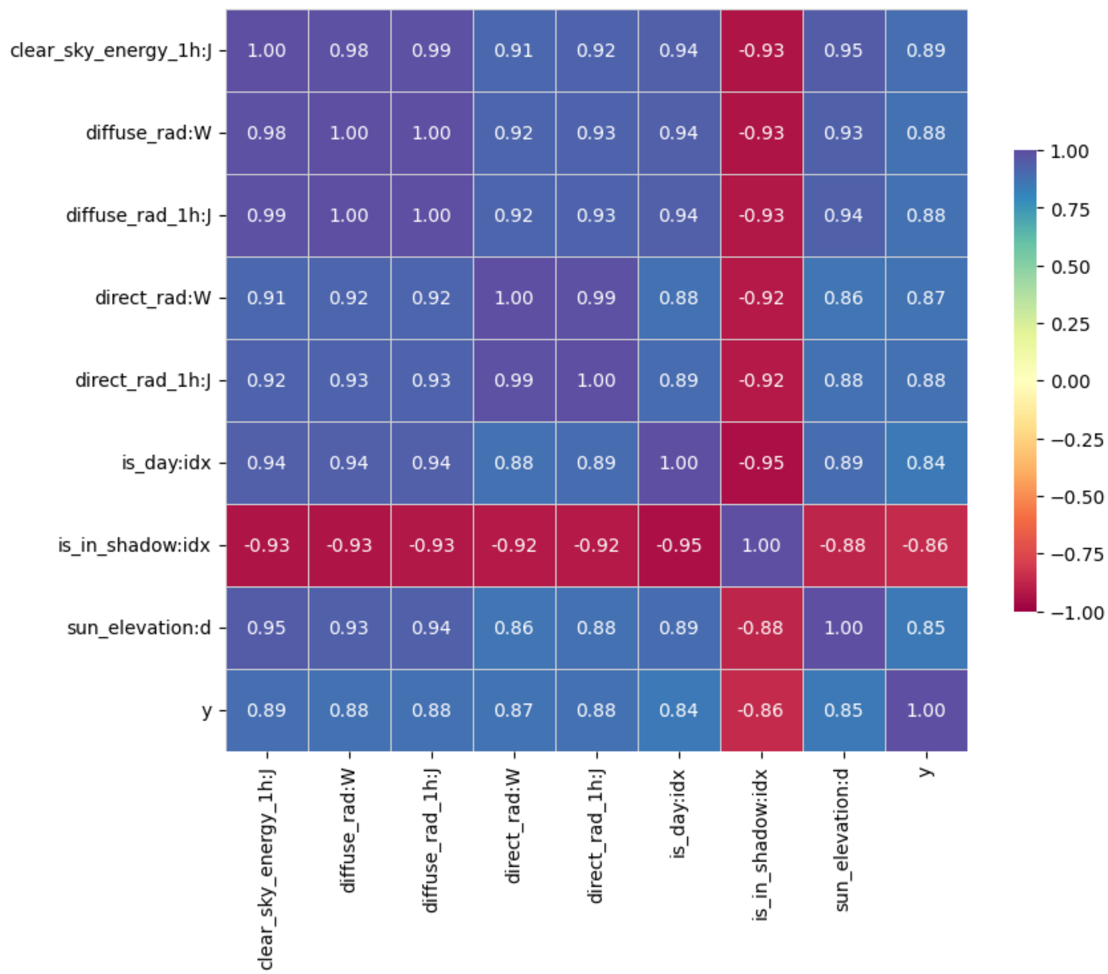


1.1.1 Distribution fits for target variable

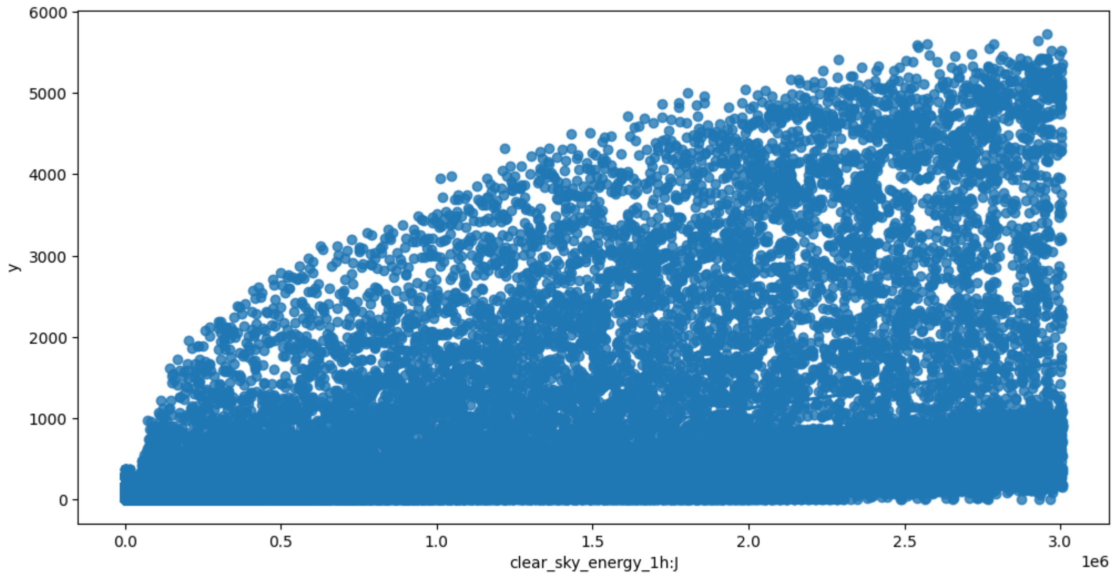
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

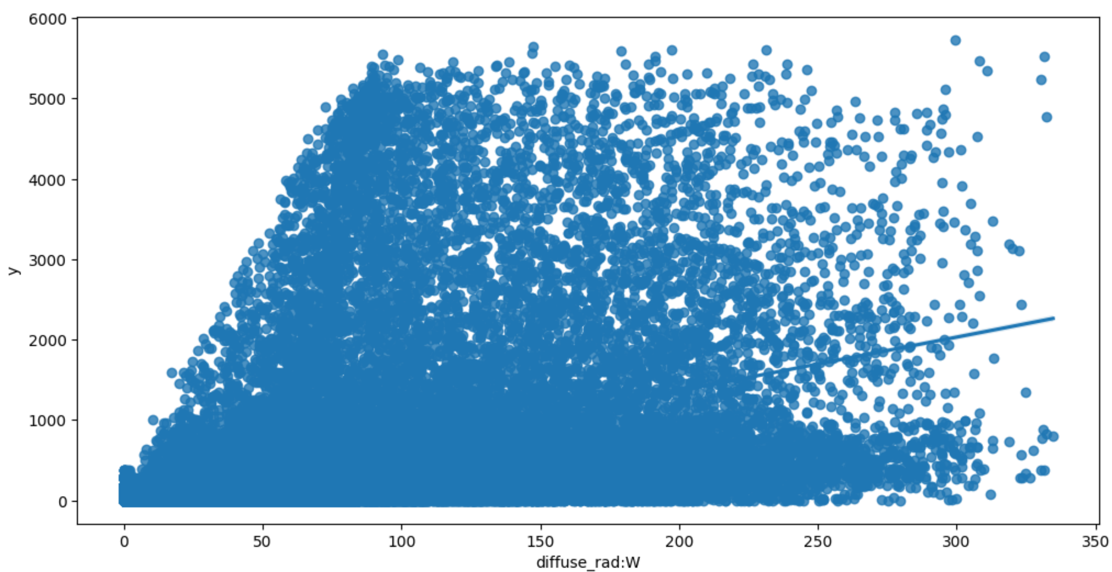
`train_data` - spearman correlation matrix; focus: absolute correlation for `y` >= `0.5`



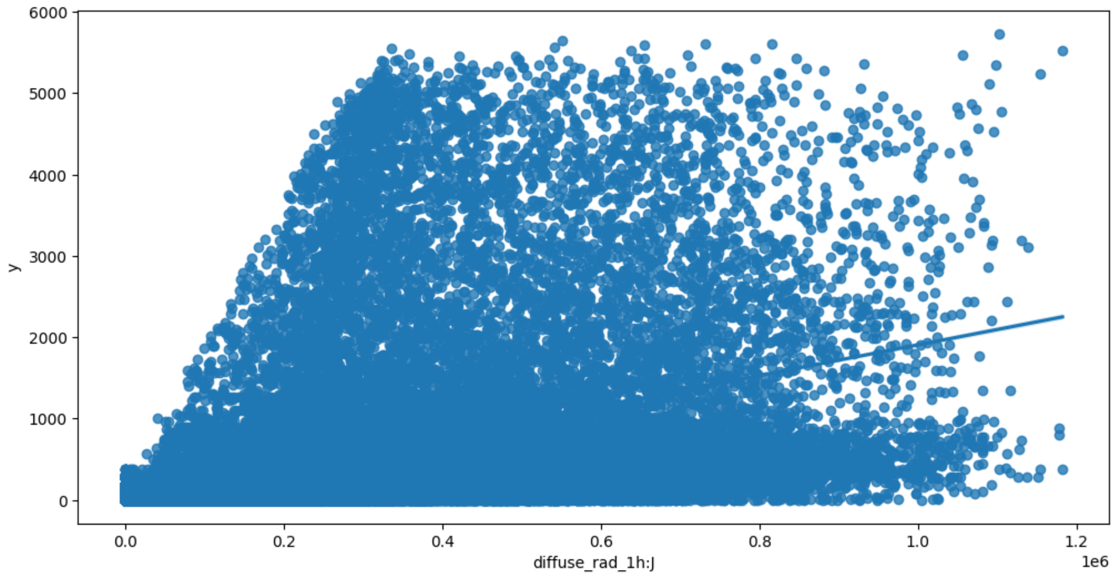
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data`



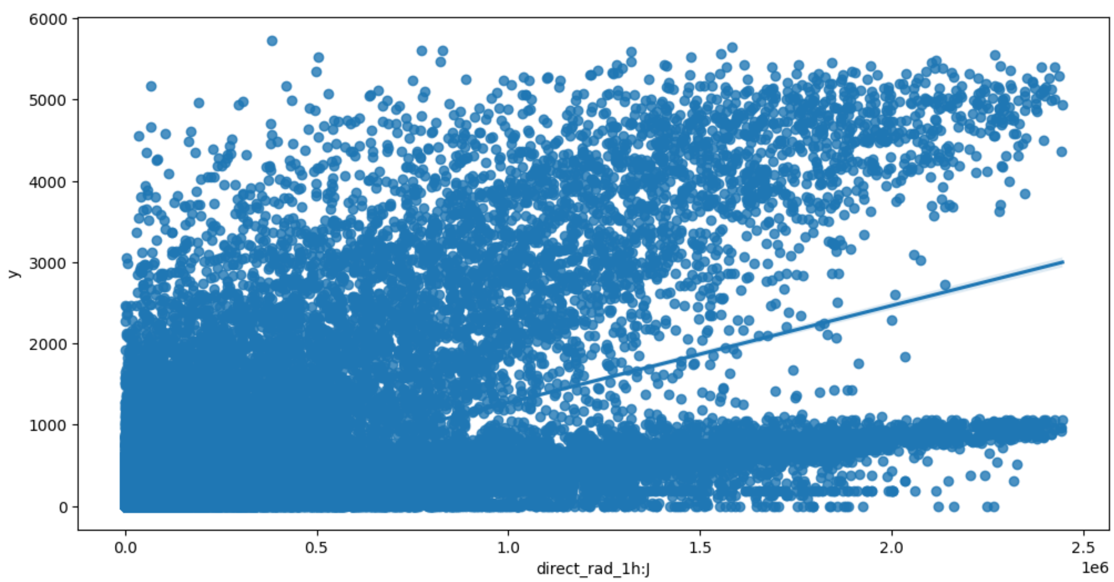
Feature interaction between `diffuse_rad:W/y` in `train_data`



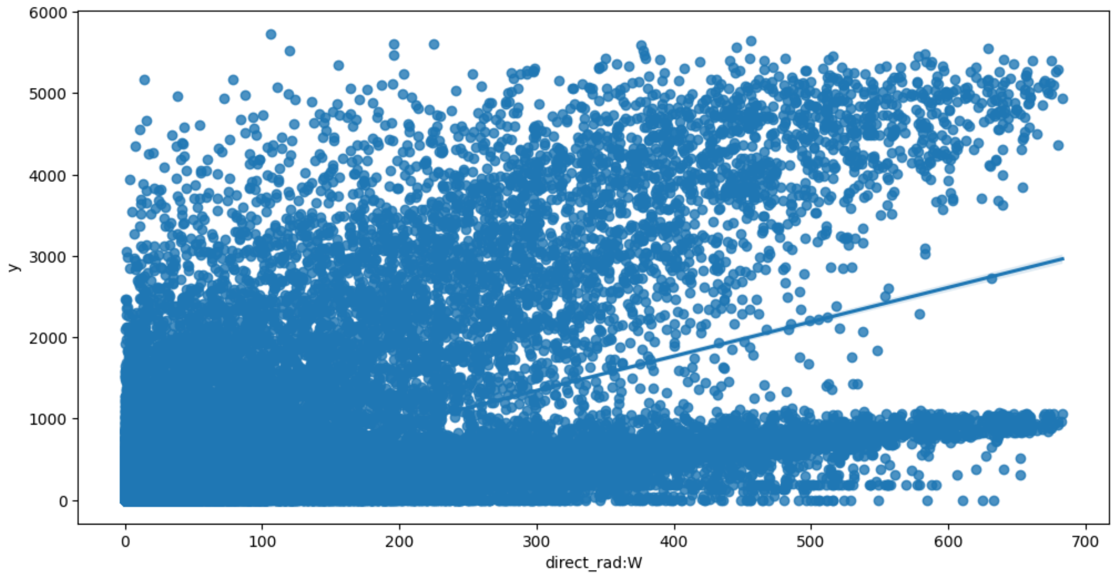
Feature interaction between `diffuse_rad_1h:J/y` in `train_data`



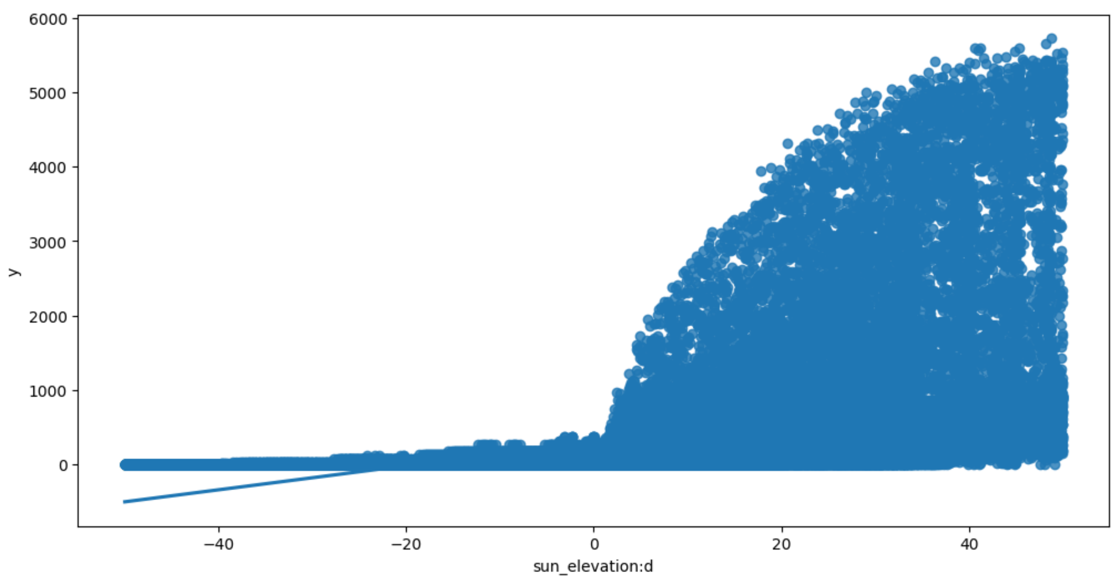
Feature interaction between `direct_rad_1h:J/y` in `train_data`



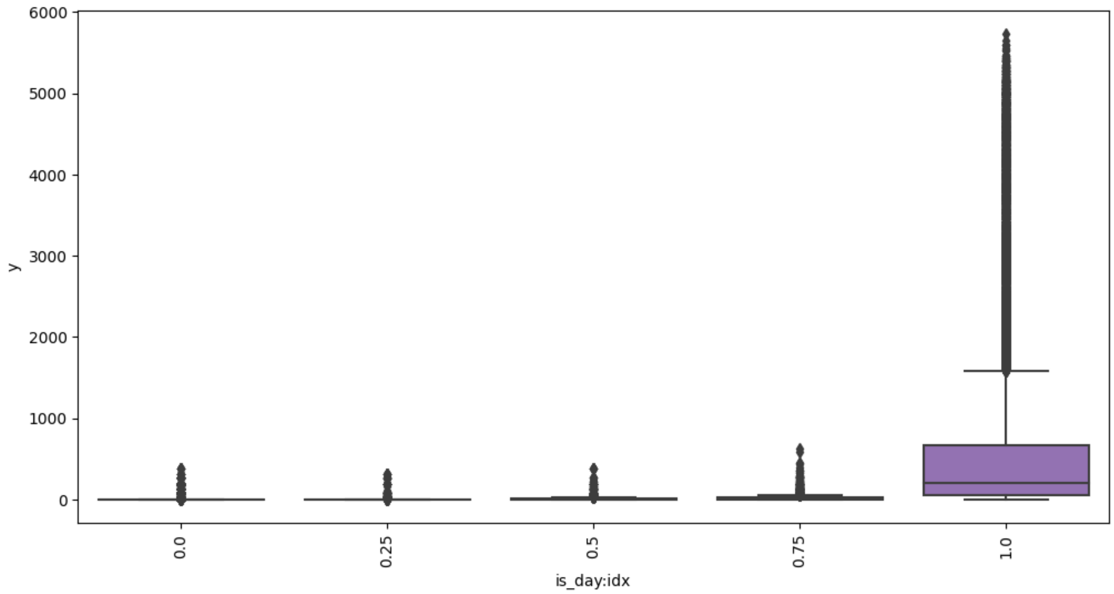
Feature interaction between `direct_rad:W/y` in `train_data`



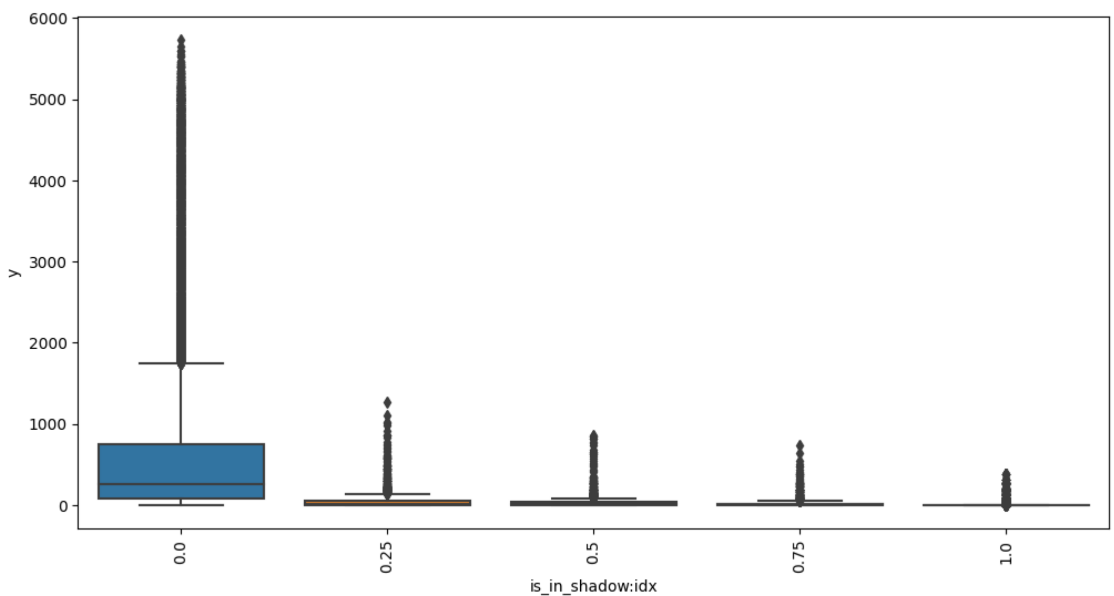
Feature interaction between `sun_elevation:d/y` in `train_data`



Feature interaction between `is_day:idx/y` in `train_data`



Feature interaction between `is_in_shadow:idx/y` in `train_data`



2 Starting

[9]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 100
Now creating submission number: 101
New filename: submission_101
```

[10]:
```
predictors = [None, None, None]
```

[ ]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
```

```
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
↪drop(columns=["ds"]),
        time_limit=time_limit,
        # presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Beginning AutoGluon training … Time limit = 1800s
AutoGluon will save models to "AutogluonModels/submission_101_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   137.83 GB / 315.93 GB (43.6%)
Train Data Rows:    31872
Train Data Columns: 28
Tuning Data Rows:     1093
Tuning Data Columns: 28
Label Column: y
```

```
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 649.68162,
1178.37671)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132236.17 MB
        Train Data (Original)  Memory Usage: 9.03 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 25 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'cloud_base_agl:m', 'diffuse_rad:W',
'diffuse_rad_1h:J', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 25 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'cloud_base_agl:m', 'diffuse_rad:W',
'diffuse_rad_1h:J', …]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        26 features in original data used to generate 26 features in processed
data.
        Train Data (Processed) Memory Usage: 6.63 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.15s …
AutoGluon will gauge predictive performance using evaluation metric:
```

```
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}

Training model for location A…

Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 1799.85s of
the 1799.85s of remaining time.
        -140.7607        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.37s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 1799.34s of
the 1799.34s of remaining time.
        -140.9568        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.37s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1798.88s of the
1798.88s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -95.4279         = Validation score   (-mean_absolute_error)
        30.28s   = Training   runtime
        12.83s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1759.26s of the
```

```
1759.26s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -98.3654         = Validation score   (-mean_absolute_error)
        23.39s   = Training   runtime
        3.38s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 1732.6s of
the 1732.6s of remaining time.
        -109.0003        = Validation score   (-mean_absolute_error)
        6.33s    = Training   runtime
        1.19s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1723.76s of the
1723.75s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -105.2989        = Validation score   (-mean_absolute_error)
        190.92s  = Training   runtime
        0.11s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 1531.67s of the
1531.66s of remaining time.
        -113.7193        = Validation score   (-mean_absolute_error)
        1.45s    = Training   runtime
        1.18s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1527.68s of
the 1527.68s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -108.1271        = Validation score   (-mean_absolute_error)
        38.92s   = Training   runtime
        0.56s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1486.97s of the
1486.97s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -102.6135        = Validation score   (-mean_absolute_error)
        8.73s    = Training   runtime
        0.34s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1476.11s of
the 1476.11s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -95.0881         = Validation score   (-mean_absolute_error)
        107.54s  = Training   runtime
        0.37s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1367.18s of the
1367.17s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -97.7935         = Validation score   (-mean_absolute_error)
        90.77s   = Training   runtime
        17.6s    = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1266.0s of the
1265.99s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -95.1885         = Validation score   (-mean_absolute_error)
        61.78s   = Training   runtime
        23.97s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1228.88s of the
1228.88s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -97.9718         = Validation score   (-mean_absolute_error)
        46.17s   = Training   runtime
        8.24s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1201.53s of the
1201.53s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -105.2287        = Validation score   (-mean_absolute_error)
        383.15s  = Training   runtime
        0.2s     = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1007.86s of
the 1007.85s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -108.1618        = Validation score   (-mean_absolute_error)
        78.38s   = Training   runtime
        1.1s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 965.99s of the
965.98s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -102.2023        = Validation score   (-mean_absolute_error)
        17.15s   = Training   runtime
        0.73s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 955.96s of the
955.96s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```
import matplotlib.pyplot as plt

leaderboards = [None, None, None]
```

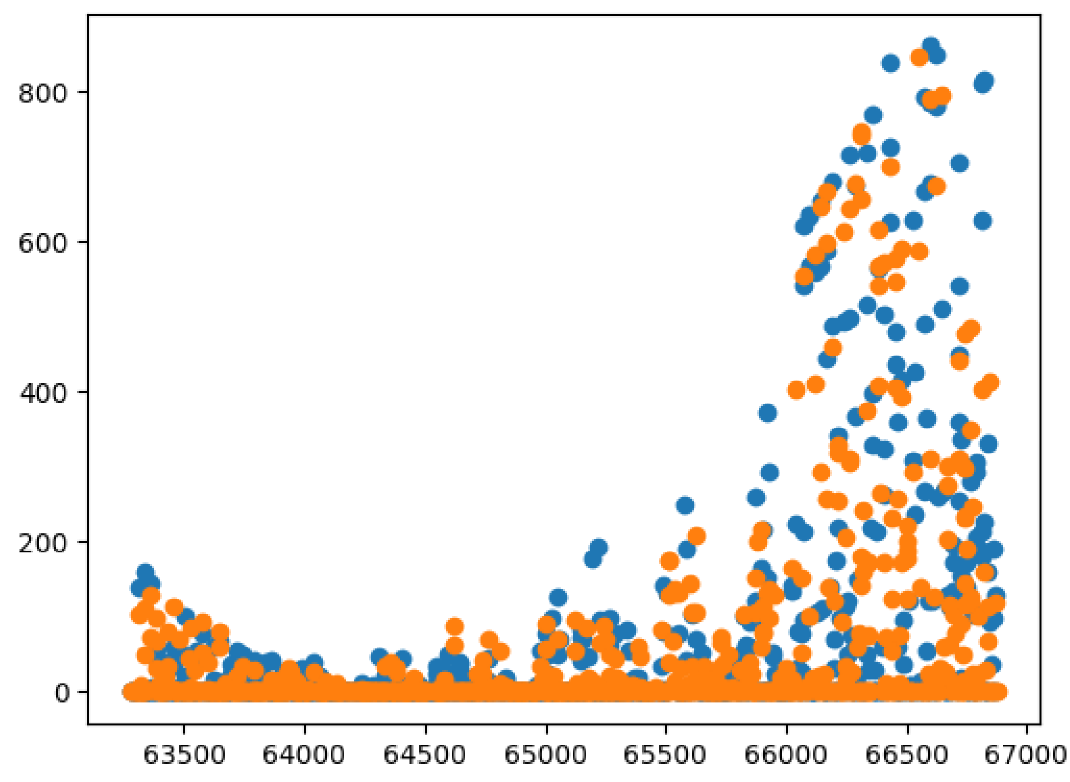
```
def leaderboard_for_location(i, loc):
    if use_test_data:
        lb = predictors[i].leaderboard(test_data[test_data["location"] == loc])
        lb["location"] = loc
        plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
↪test_data[test_data["location"] == loc]["y"])
        if use_tune_data:
            plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,␣
↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.show()

        return lb
    else:
        return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```

[13]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

```
        -16.3215         = Validation score   (-mean_absolute_error)
        385.35s  = Training   runtime
        0.21s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 854.02s of
the 854.02s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.193  = Validation score   (-mean_absolute_error)
        77.43s   = Training   runtime
        1.05s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 812.89s of the
812.88s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.1244         = Validation score   (-mean_absolute_error)
        152.45s  = Training   runtime
        48.94s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 728.57s of the
728.57s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.751  = Validation score   (-mean_absolute_error)
        351.21s  = Training   runtime
        0.66s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 550.0s of the
550.0s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
```

```
ParallelLocalFoldFittingStrategy
        -14.2513         = Validation score   (-mean_absolute_error)
        186.52s  = Training   runtime
        41.83s   = Validation runtime
Completed 2/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
442.77s of remaining time.
        -11.6597         = Validation score   (-mean_absolute_error)
        0.43s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 1357.68s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_101_B/")
Evaluation: mean_absolute_error on test data: -14.547869225363064
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -14.547869225363064,
    "root_mean_squared_error": -44.85425668975588,
    "mean_squared_error": -2011.90434319051,
    "r2": 0.909051782885076,
    "pearsonr": 0.9548156385330459,
    "median_absolute_error": -0.37705013155937195
}

Evaluation on test data:
-14.547869225363064
                     model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0    NeuralNetTorch_BAG_L1  -14.489736 -11.751021        0.351410       0.662124
351.210851                 0.351410                0.662124         351.210851
1       True        10
1      WeightedEnsemble_L2  -14.547869 -11.659718        1.207992       2.057405
738.400992                 0.003429                0.000540           0.426711
2       True        12
2   NeuralNetFastAI_BAG_L1  -16.326178 -14.193033        1.020282       1.049720
77.426473                 1.020282                1.049720         77.426473
1       True         8
3     LightGBMLarge_BAG_L1  -16.867807 -14.251304        8.466552      41.832313
186.524971                 8.466552               41.832313        186.524971
1       True        11
4           XGBoost_BAG_L1  -17.886484 -15.124446        4.588538      48.941980
152.446251                 4.588538               48.941980        152.446251
1       True         9
5          LightGBM_BAG_L1  -18.015132 -15.396378        2.733061      25.483243
```

```
60.669254                 2.733061              25.483243          60.669254
1       True            4
6           CatBoost_BAG_L1  -18.516337 -16.321547         0.191183       0.214026
385.354122                 0.191183               0.214026          385.354122
1       True            6
7         LightGBMXT_BAG_L1  -19.090083 -15.743320         2.770541      29.846826
58.484428                 2.770541              29.846826          58.484428
1       True            3
8      ExtraTreesMSE_BAG_L1  -19.373523 -15.172927         0.661969       1.180715
1.409308                 0.661969              1.180715           1.409308
1       True            7
9    RandomForestMSE_BAG_L1  -20.019074 -15.782449         0.560164       1.152136
7.220658                 0.560164              1.152136           7.220658
1       True            5
10   KNeighborsDist_BAG_L1  -30.089573 -23.622609         0.017341       1.242610
0.026984                 0.017341              1.242610           0.026984
1       True            2
11   KNeighborsUnif_BAG_L1  -30.135864 -23.684113         0.019941       0.452281
0.028449                 0.019941              0.452281           0.028449
1       True            1
```



[14]:
```python
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Beginning AutoGluon training … Time limit = 1800s
AutoGluon will save models to "AutogluonModels/submission_101_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   129.79 GB / 315.93 GB (41.1%)
Train Data Rows:    24594
Train Data Columns: 28
Tuning Data Rows:    737
Tuning Data Columns: 28
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 79.8926, 168.407)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130059.28 MB
        Train Data (Original)  Memory Usage: 6.94 MB (0.0% of available memory)

Training model for location C…

        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
```

```
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 25 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'cloud_base_agl:m', 'diffuse_rad:W',
'diffuse_rad_1h:J', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 25 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'cloud_base_agl:m', 'diffuse_rad:W',
'diffuse_rad_1h:J', …]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        26 features in original data used to generate 26 features in processed
data.
        Train Data (Processed) Memory Usage: 5.09 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 1799.87s of
the 1799.87s of remaining time.
```

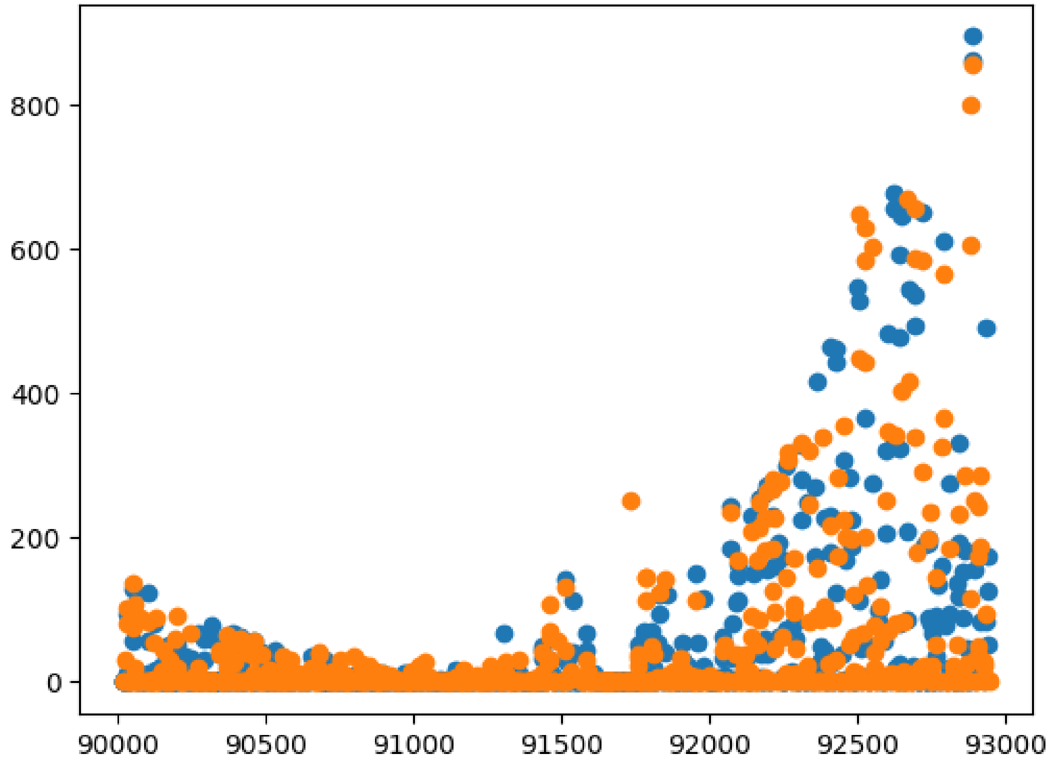
```
        -23.649  = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.27s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 1799.52s of
the 1799.52s of remaining time.
        -23.7005         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.34s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1799.1s of the
1799.1s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.464  = Validation score   (-mean_absolute_error)
        27.71s   = Training   runtime
        9.72s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1767.42s of the
1767.42s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.7205         = Validation score   (-mean_absolute_error)
        26.49s   = Training   runtime
        6.44s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 1737.52s of
the 1737.52s of remaining time.
        -16.4245         = Validation score   (-mean_absolute_error)
        3.86s    = Training   runtime
        0.76s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1732.26s of the
1732.25s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4305         = Validation score   (-mean_absolute_error)
        184.47s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 1546.52s of the
1546.52s of remaining time.
        -16.1959         = Validation score   (-mean_absolute_error)
        0.93s    = Training   runtime
        0.78s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1544.1s of
the 1544.1s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7987         = Validation score   (-mean_absolute_error)
        31.64s   = Training   runtime
        0.42s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1510.79s of the
1510.79s of remaining time.
```

```
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.5135         = Validation score   (-mean_absolute_error)
        43.75s   = Training   runtime
        2.49s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1463.86s of
the 1463.86s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.2172         = Validation score   (-mean_absolute_error)
        92.48s   = Training   runtime
        0.26s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1369.98s of the
1369.98s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8764         = Validation score   (-mean_absolute_error)
        88.53s   = Training   runtime
        12.53s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1273.04s of the
1273.03s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.3868         = Validation score   (-mean_absolute_error)
        57.27s   = Training   runtime
        22.75s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1238.28s of the
1238.27s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.5816         = Validation score   (-mean_absolute_error)
        52.39s   = Training   runtime
        11.54s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1207.83s of the
1207.83s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3746         = Validation score   (-mean_absolute_error)
        370.14s  = Training   runtime
        0.18s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1020.81s of
the 1020.81s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7932         = Validation score   (-mean_absolute_error)
        62.91s   = Training   runtime
        0.87s    = Validation runtime
```

```
Fitting model: XGBoost_BAG_L1 … Training model for up to 987.16s of the
987.16s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.6574         = Validation score   (-mean_absolute_error)
        81.56s   = Training   runtime
        4.68s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 945.57s of the
945.57s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3958         = Validation score   (-mean_absolute_error)
        164.59s  = Training   runtime
        0.53s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 871.89s of the
871.89s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8074         = Validation score   (-mean_absolute_error)
        176.26s  = Training   runtime
        22.76s   = Validation runtime
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 772.19s of the
772.19s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.3667         = Validation score   (-mean_absolute_error)
        84.13s   = Training   runtime
        34.2s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 738.9s of the 738.9s
of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.555  = Validation score   (-mean_absolute_error)
        76.32s   = Training   runtime
        16.14s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 709.54s of the
709.54s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3762         = Validation score   (-mean_absolute_error)
        555.1s   = Training   runtime
        0.27s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 523.16s of
the 523.16s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7958         = Validation score   (-mean_absolute_error)
```

```
        94.98s   = Training   runtime
        1.28s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 488.47s of the
488.47s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.612  = Validation score   (-mean_absolute_error)
        124.68s  = Training   runtime
        6.1s     = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 440.97s of the
440.97s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3421         = Validation score   (-mean_absolute_error)
        251.81s  = Training   runtime
        0.79s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 352.05s of the
352.04s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8232         = Validation score   (-mean_absolute_error)
        262.66s  = Training   runtime
        33.03s   = Validation runtime
Completed 3/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
250.2s of remaining time.
        -11.6491         = Validation score   (-mean_absolute_error)
        0.43s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 1550.25s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_101_C/")
Evaluation: mean_absolute_error on test data: -11.584846974967073
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -11.584846974967073,
    "root_mean_squared_error": -33.28157104597867,
    "mean_squared_error": -1107.662971288526,
    "r2": 0.9119603983629877,
    "pearsonr": 0.9553301989877001,
    "median_absolute_error": -0.5380167663097382
}

Evaluation on test data:
-11.584846974967073
```

	model	score_test	score_val	pred_time_test	pred_time_val	fit_time	pred_time_test_marginal	pred_time_val_marginal	fit_time_marginal	stack_level	can_infer	fit_order
0	WeightedEnsemble_L2	-11.584847	-11.649102	15.890272	68.017162	599.024821	0.003410	0.000649	0.426667	2	True	12
1	LightGBMXT_BAG_L1	-12.414818	-12.366686	5.450568	34.196357	84.132116	5.450568	34.196357	84.132116	1	True	3
2	LightGBMLarge_BAG_L1	-12.543343	-12.823171	9.914580	33.028136	262.660037	9.914580	33.028136	262.660037	1	True	11
3	NeuralNetTorch_BAG_L1	-12.844010	-13.342115	0.521714	0.792019	251.806001	0.521714	0.792019	251.806001	1	True	10
4	LightGBM_BAG_L1	-13.018393	-13.555035	4.026720	16.135706	76.315174	4.026720	16.135706	76.315174	1	True	4
5	XGBoost_BAG_L1	-13.618762	-13.612037	1.837001	6.100511	124.681797	1.837001	6.100511	124.681797	1	True	9
6	CatBoost_BAG_L1	-13.908382	-13.376167	0.210222	0.273467	555.101594	0.210222	0.273467	555.101594	1	True	6
7	NeuralNetFastAI_BAG_L1	-14.484465	-14.795795	1.373520	1.280287	94.977746	1.373520	1.280287	94.977746	1	True	8
8	ExtraTreesMSE_BAG_L1	-15.827128	-16.195930	0.396986	0.775828	0.931813	0.396986	0.775828	0.931813	1	True	7
9	RandomForestMSE_BAG_L1	-16.451605	-16.424500	0.334966	0.761000	3.862862	0.334966	0.761000	3.862862	1	True	5
10	KNeighborsDist_BAG_L1	-23.919280	-23.700527	0.013227	0.338030	0.021528	0.013227	0.338030	0.021528	1	True	2
11	KNeighborsUnif_BAG_L1	-24.102600	-23.649027	0.028486	0.269659	0.020741	0.028486	0.269659	0.020741	1	True	1



[ ]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

future_test_data = TabularDataset('X_test_raw.csv')
future_test_data["ds"] = pd.to_datetime(future_test_data["ds"])
#test_data
```

```
Loaded data from: X_test_raw.csv | Columns = 29 / 29 | Rows = 4608 -> 4608
```

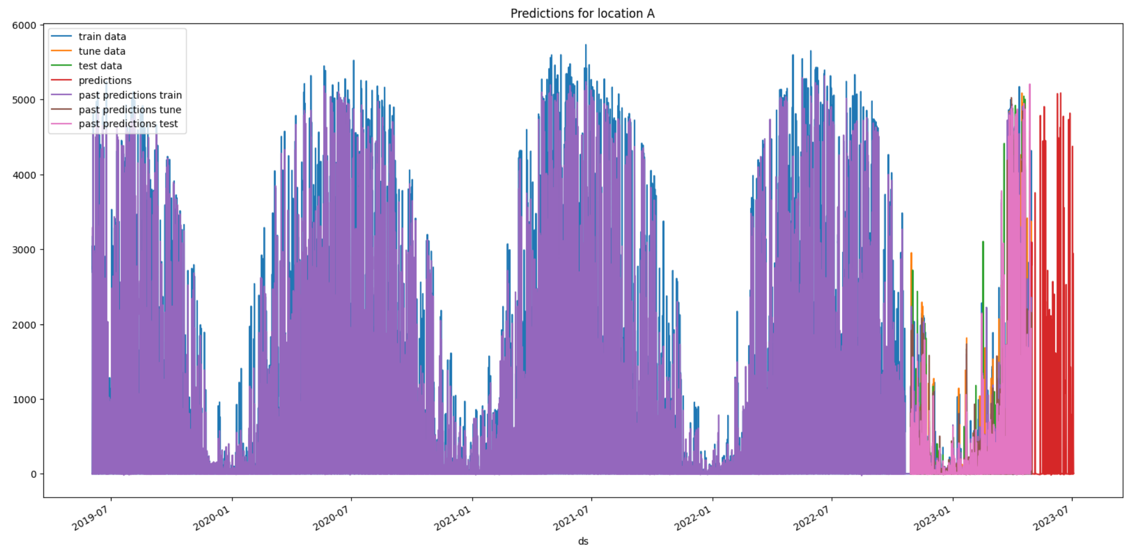
[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
future_test_data_merged = pd.merge(future_test_data, test_ids, how="inner",␣
↪right_on=["time", "location"], left_on=["ds", "location"])

#test_data_merged
```

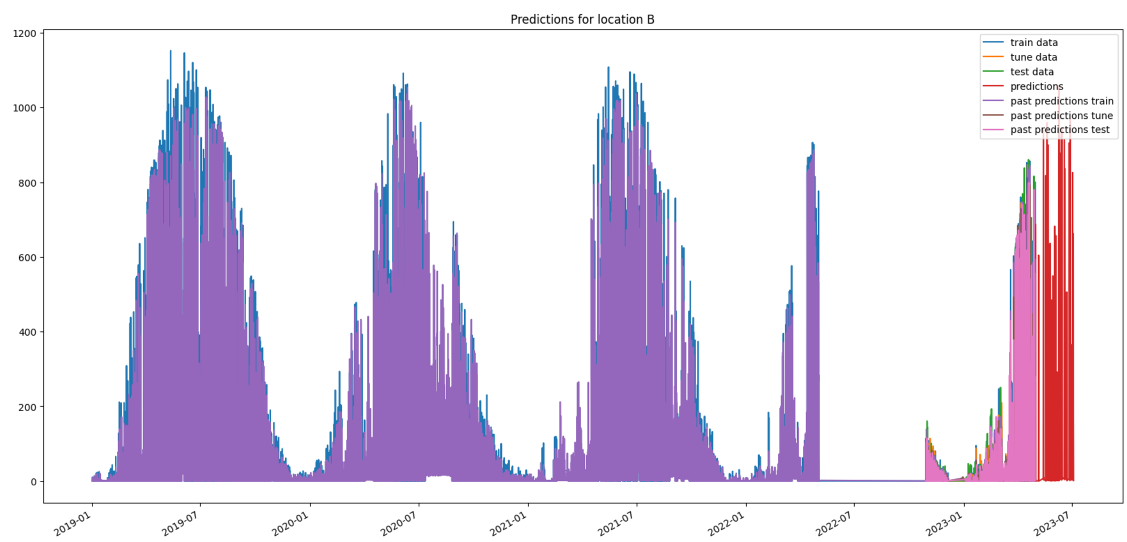
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

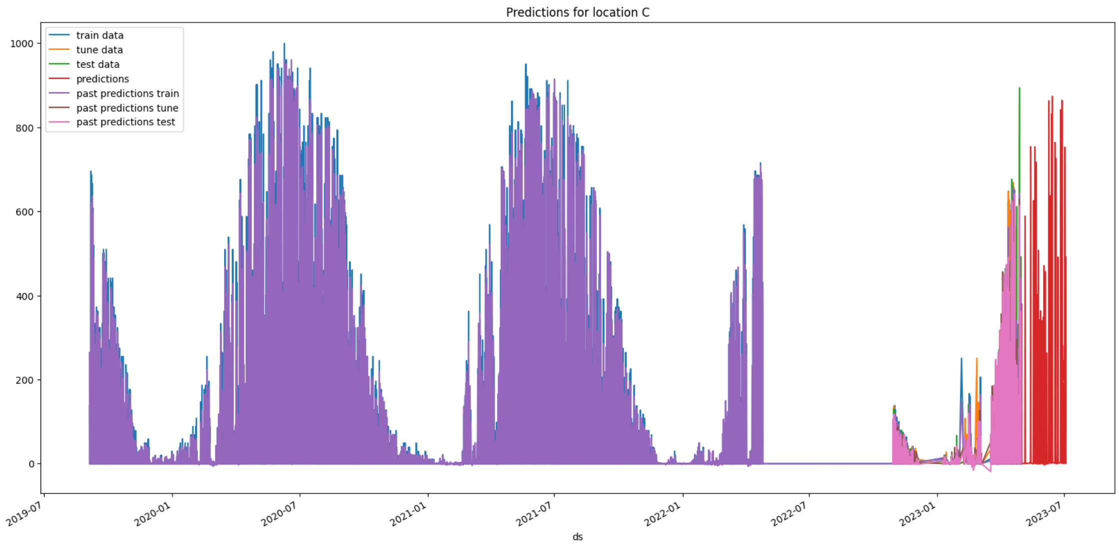
[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in future_test_data.groupby('location'):
    i = location_map[loc]
    subset = future_test_data_merged[future_test_data_merged["location"] ==␣
↪loc].reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    train_data.loc[train_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(train_data[train_data["location"] == loc])
    if use_tune_data:
        tuning_data.loc[tuning_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(tuning_data[tuning_data["location"] == loc])
    if use_test_data:
        test_data.loc[test_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(test_data[test_data["location"] == loc])
```

[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data[train_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="train data")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="tune data")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="test data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    #train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")
```

```
    train_data[train_data["location"]==loc].plot(x='ds', y='prediction', ax=ax,␣
↪label="past predictions train")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions tune")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions test")


    # title
    ax.set_title(f"Predictions for location {loc}")
```







[ ]:
```
temp_predictions = [prediction.copy() for prediction in predictions]
if clip_predictions:
    # clip predictions smaller than 0 to 0
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())

# Instead of clipping, shift all prediction values up by the largest negative␣
 ↪number.
# This way, the smallest prediction will be 0.
elif shift_predictions:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred["prediction"] = pred["prediction"] - pred["prediction"].min()
        print("Smallest prediction after clipping:", pred["prediction"].min())

elif shift_predictions_by_average_of_negatives_then_clip:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        mean_negative = pred[pred["prediction"] < 0]["prediction"].mean()
        # if not nan
        if mean_negative == mean_negative:
```

```
            pred["prediction"] = pred["prediction"] - mean_negative

        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())



# concatenate predictions
submissions_df = pd.concat(temp_predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

```
Smallest prediction: -16.878181
Smallest prediction after clipping: 0.0
Smallest prediction: 0.07609784
Smallest prediction after clipping: 0.07609784
Smallest prediction: -3.4177196
Smallest prediction after clipping: 0.0
```

[ ]:

```
       id  prediction
0       0    0.000000
1       1    0.000000
2       2    0.000000
3       3   61.788113
4       4  296.051880
..    …         …
715  2155   70.078865
716  2156   43.007858
717  2157   10.200218
718  2158    4.401361
719  2159    0.849800

[2160 rows x 2 columns]
```

[ ]:

```
# Save the submission DataFrame to submissions folder, create new name based on
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
 ↪index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_101.csv
jall1a
```

[ ]:

```
train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])
```

```python
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
 ↪time_limit=60*10)
```

```
Loaded data from: X_train_raw.csv | Columns = 30 / 30 | Rows = 92945 -> 92945
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location']
Computing feature importance via permutation shuffling for 26 features using
4392 rows with 10 shuffle sets… Time limit: 600s…
        1858.07s        = Expected runtime (185.81s per shuffle set)
        564.33s = Actual runtime (Completed 5 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[ ]:

	importance	stddev	p_value	n	\
direct_rad_1h:J	174.758804	1.385776	4.744175e-10	5	
clear_sky_energy_1h:J	120.681118	1.767450	5.519356e-09	5	
diffuse_rad_1h:J	91.116242	1.237380	4.080410e-09	5	
diffuse_rad:W	84.881611	1.184729	4.552924e-09	5	
direct_rad:W	80.238447	1.949325	4.176824e-08	5	
sun_elevation:d	61.935056	1.761940	7.851108e-08	5	
sun_azimuth:d	51.658621	3.061597	1.473570e-06	5	
effective_cloud_cover:p	29.954183	1.199781	3.081984e-07	5	
sfc_pressure:hPa	20.717220	2.138205	1.342484e-05	5	
total_cloud_cover:p	19.316892	0.960869	7.322466e-07	5	
is_in_shadow:idx	15.526777	0.518693	1.492284e-07	5	
snow_water:kgm2	14.541732	0.706230	6.654835e-07	5	
relative_humidity_1000hPa:p	13.896670	0.740659	9.646449e-07	5	
t_1000hPa:K	13.122288	1.133759	6.620869e-06	5	
visibility:m	12.813578	0.989004	4.225220e-06	5	
ceiling_height_agl:m	12.175750	0.728600	1.531388e-06	5	
cloud_base_agl:m	12.174280	0.614288	7.752191e-07	5	
wind_speed_10m:ms	9.728451	0.535143	1.094294e-06	5	
is_day:idx	8.864305	0.477792	1.008965e-06	5	
fresh_snow_6h:cm	8.810844	0.434730	7.088907e-07	5	
super_cooled_liquid_water:kgm2	5.405043	0.792973	5.403276e-05	5	
precip_type_5min:idx	5.397076	0.817897	6.139860e-05	5	
fresh_snow_3h:cm	2.969766	0.446444	5.948215e-05	5	
snow_depth:cm	2.947989	0.649037	2.646037e-04	5	
fresh_snow_1h:cm	2.447736	0.362044	5.579644e-05	5	
is_estimated	0.000000	0.000000	5.000000e-01	5	

	p99_high	p99_low
direct_rad_1h:J	177.612136	171.905472

```
clear_sky_energy_1h:J           124.320322  117.041914
diffuse_rad_1h:J                 93.664025   88.568460
diffuse_rad:W                    87.320985   82.442237
direct_rad:W                     84.252133   76.224761
sun_elevation:d                  65.562914   58.307197
sun_azimuth:d                    57.962491   45.354751
effective_cloud_cover:p          32.424548   27.483818
sfc_pressure:hPa                 25.119813   16.314627
total_cloud_cover:p              21.295334   17.338449
is_in_shadow:idx                 16.594773   14.458781
snow_water:kgm2                  15.995870   13.087594
relative_humidity_1000hPa:p      15.421696   12.371643
t_1000hPa:K                      15.456713   10.787864
visibility:m                     14.849950   10.777206
ceiling_height_agl:m             13.675948   10.675552
cloud_base_agl:m                 13.439108   10.909451
wind_speed_10m:ms                10.830317    8.626585
is_day:idx                        9.848084    7.880525
fresh_snow_6h:cm                  9.705959    7.915730
super_cooled_liquid_water:kgm2    7.037786    3.772300
precip_type_5min:idx              7.081137    3.713015
fresh_snow_3h:cm                  3.889001    2.050532
snow_depth:cm                     4.284365    1.611613
fresh_snow_1h:cm                  3.193190    1.702281
is_estimated                      0.000000    0.000000
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location']
Computing feature importance via permutation shuffling for 26 features using
5000 rows with 10 shuffle sets… Time limit: 600s…
        2130.12s        = Expected runtime (213.01s per shuffle set)
        569.03s = Actual runtime (Completed 4 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[ ]:
```
                                  importance        stddev       p_value  n  \
direct_rad_1h:J                 2.979640e+02  7.742726e+00  2.417003e-06  4
clear_sky_energy_1h:J           2.209681e+02  9.822432e+00  1.208502e-05  4
diffuse_rad_1h:J                1.407333e+02  7.063642e+00  1.738850e-05  4
diffuse_rad:W                   1.374164e+02  7.932426e+00  2.643334e-05  4
sun_elevation:d                 1.086858e+02  7.045457e+00  3.740413e-05  4
direct_rad:W                    1.079841e+02  3.567674e+00  4.965927e-06  4
sun_azimuth:d                   1.000221e+02  4.298227e+00  1.091969e-05  4
```

effective_cloud_cover:p	5.132260e+01	1.807393e+00	6.013092e-06	4
t_1000hPa:K	4.585019e+01	9.698193e-01	1.303842e-06	4
ceiling_height_agl:m	3.442258e+01	1.177199e+00	5.506973e-06	4
sfc_pressure:hPa	3.296733e+01	1.655336e+00	1.740897e-05	4
visibility:m	3.234283e+01	1.613807e+00	1.708438e-05	4
relative_humidity_1000hPa:p	3.163136e+01	1.637891e+00	1.908995e-05	4
wind_speed_10m:ms	2.991173e+01	1.924733e-01	3.672161e-08	4
cloud_base_agl:m	2.981524e+01	1.391653e+00	1.398871e-05	4
total_cloud_cover:p	2.653299e+01	1.212222e+00	1.311967e-05	4
snow_water:kgm2	2.382866e+01	1.286464e+00	2.163251e-05	4
precip_type_5min:idx	2.226013e+01	1.505111e+00	4.243157e-05	4
super_cooled_liquid_water:kgm2	2.057215e+01	7.752532e-01	7.366942e-06	4
is_in_shadow:idx	1.950323e+01	2.203955e+00	1.966394e-04	4
is_day:idx	1.233222e+01	1.283926e+00	1.540374e-04	4
fresh_snow_6h:cm	2.728599e+00	3.015600e-01	1.840345e-04	4
snow_depth:cm	1.646735e+00	3.652632e-01	1.440103e-03	4
fresh_snow_3h:cm	6.826377e-01	3.024028e-01	1.015541e-02	4
fresh_snow_1h:cm	4.674250e-01	2.723762e-01	2.073566e-02	4
is_estimated	5.015735e-09	1.799561e-08	3.080590e-01	4

	p99_high	p99_low
direct_rad_1h:J	3.205763e+02	2.753517e+02
clear_sky_energy_1h:J	2.496540e+02	1.922821e+02
diffuse_rad_1h:J	1.613624e+02	1.201043e+02
diffuse_rad:W	1.605827e+02	1.142501e+02
sun_elevation:d	1.292618e+02	8.810988e+01
direct_rad:W	1.184033e+02	9.756485e+01
sun_azimuth:d	1.125748e+02	8.746929e+01
effective_cloud_cover:p	5.660100e+01	4.604419e+01
t_1000hPa:K	4.868250e+01	4.301788e+01
ceiling_height_agl:m	3.786053e+01	3.098462e+01
sfc_pressure:hPa	3.780166e+01	2.813300e+01
visibility:m	3.705588e+01	2.762978e+01
relative_humidity_1000hPa:p	3.641475e+01	2.684798e+01
wind_speed_10m:ms	3.047384e+01	2.934962e+01
cloud_base_agl:m	3.387950e+01	2.575098e+01
total_cloud_cover:p	3.007323e+01	2.299276e+01
snow_water:kgm2	2.758572e+01	2.007160e+01
precip_type_5min:idx	2.665574e+01	1.786453e+01
super_cooled_liquid_water:kgm2	2.283625e+01	1.830806e+01
is_in_shadow:idx	2.593978e+01	1.306668e+01
is_day:idx	1.608187e+01	8.582576e+00
fresh_snow_6h:cm	3.609291e+00	1.847907e+00
snow_depth:cm	2.713470e+00	5.800004e-01
fresh_snow_3h:cm	1.565791e+00	-2.005158e-01
fresh_snow_1h:cm	1.262887e+00	-3.280375e-01
is_estimated	5.757109e-08	-4.753962e-08

[ ]:
```python
# save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

```
<IPython.core.display.Javascript object>
```

[ ]:
```python
# save this notebook to submissions folder
import subprocess
import os
#subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
/opt/conda/lib/python3.10/site-packages/nbconvert/utils/pandoc.py:51:
RuntimeWarning: You are using an unsupported version of pandoc (2.9.2.1).
Your version must be at least (2.14.2) but less than (4.0.0).
Refer to https://pandoc.org/installing.html.
Continuing with doubts…
  check_pandoc_version()
[NbConvertApp] Support files will be in notebook_pdfs/submission_101_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_101_files/notebook_pdfs
[NbConvertApp] Writing 183909 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1904761 bytes to notebook_pdfs/submission_101.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_101.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[ ]:
```python
# display(Javascript("IPython.notebook.save_checkpoint();"))
# time.sleep(3)

# subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command, stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email', 'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push', 'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream', 'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```

[ ]:
```
```

[ ]:
```

```
[ ]:
```

```
[ ]:
```

```